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Automated and Robust Brain Skull Stripping using Optimized Pre-processing and a Refined Residual U-Net Framework

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Abstract

In this study, a method for skull stripping referred to as the 3D Enhanced Residual U-Net is introduced. The approach combines the traditional U-Net with an enhancement mechanism designed to improve both the effectiveness and processing speed of the U-Net. An anisotropic diffusion filter (ADF) reduces noise in MRI images while maintaining the edges of present objects. This is accompanied by skull stripping to eliminate non-brain matter and contrast enhancement to elevate the visual quality. The architectural adaptations allow for rapid and stable training. As brain images vary significantly from subject to subject, a deep learning approach will account for these differences leading to consistent skull stripping results. Neurofeedback Skull Stripping (NFBS) dataset was used for the proposed model formulation. The results from the experiments show that the proposed approach is effective and practical compared to previous methods. This method obtained an impressive sensitivity rate of 0.9974, DSC of 1.0000, a specificity of 0.9983, an IOU of 0.9831, an accuracy percentage of 0.9969, and a precision of 0.9961, showing an actual ability to differentiate the distinct parts of the brain and the skull.

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1. INTRODUCTION

Automated brain skull stripping is a technique used extensively in medical imaging, especially in neuroimaging applications, including brain tissue segmentation, diagnosing diseases, and planning surgeries. This process involves removing non-brain tissues including the skull, scalp, and other peripheral structures from brain images in order to better visualize brain tissues. Whilst watershed segmentation and morphological operations have been used for older procedures, such methods are often limited by the complex anatomical variations of different individuals and are less sensitive to potential defects, leading to inaccurate detection and the difficulty of performing them successfully [1]. Very recently, CNNs possess superior capability for brain extraction using deep learning techniques, delivering improved accuracy, robustness, and automation [2].

One such approach used when performing deep learning tasks for segmentation of medical images is the U-Net structure, which was originally considered for image segmentation in medical applications [3].

The U-Net model encoder-decoder model is so far widely used because of its capability to learn spatial hierarchies and fine-grained features while computationally efficient. But U-Net does have many limitations, including the vanishing gradient, and, in particular, cannot capture long-range dependencies well, especially in deep networks (see Fig.5). In order to alleviate these challenges, suggestions included such changes as adding the presence of residual connections. Residual U-Net (R-U-Net) architecture contains residual blocks as well, making deeper networks able to learn faster without gradient problems [4]. These residual connections serve to maintain important feature maps and improve convergence and the performance of the network, particularly on more complex tasks, such as brain skull stripping where attention to detail is of utmost importance. With regards to medical imaging segmentation, residual U-Net performed well and can be tailored to improve the accuracy of skull stripping, mainly in brain tumor segmentation [5].

In this paper we first postulated a 3D residual U-Net architecture of the skull stripping system in 3D in memory to be used for automated removal of the brain skull. The most important modification is adding a residual mechanism that allows the model to concentrate on the relevant content, while minimizing distractions from irrelevant ones.

The main contributions proposed methods described to us can be summarized as follows.

1. For the task of skull stripping, an improved form of the 3D Enhanced Residual U-Net is employed. The inclusion of the residual connections makes the architecture incorporate more complicated and more detailed features that improve its robustness and accuracy when dealing with diverse and complicated brain images. These associations also help to alleviate issues such as vanishing gradients, and to more easily model better and more general neural networks.
2. The 3D U-Net is already a suitable basis for volumetric information capture and including residual connections enables an efficient knowledge acquisition and keeping of fundamental attribute. Such changes also minimize the risks of overfitting and improve its accuracy on test data new to the framework.
3. ADF is used to produce an image, free from noise while preserving important information and resulting in highly detailed images are obtained, that are information rich for skull extraction and segmentation process.
4. A morphological expanse is utilized to remove the remaining brain tissue and refine the tumor area (morphologies) to focus more effectively on the tumor tissue and extract the tumor characteristics.
5. Generalization across subject variability because of the large anatomical variation among individuals, the conventional approaches often lack the ability to generalize well. Our deep learning technique successfully controls this variability, achieving a consistent skull stripping ability over a wide range of Magnetic Resonance Imaging (MRI) samples.

The remaining of this paper is organized as follows: Section 2 presents a compilation of pertinent literature. Section 3 details the characteristics of the proposed 3D Residual U-Net approach. This method implementation is discussed in Section 4, while Section 5 addresses the testing procedures for skull stripping. Lastly, the study's conclusions are presented in Section 6.

2. RELATED WORKS

Skull stripping was done manually or with thresholds in the past, but deep learning techniques like U-Net and its variants have greatly increased the automation and precision of numerous operations like skull stripping. A convolutional neural network (CNN) designed for MRI brain extraction was introduced by Oeslle et al. in 2019 [6]. It is entirely trained utilizing what is referred to as "silver standard" masks. Therefore, handwritten annotation relates to the elimination of the expense. In the Simultaneous, the Truth and Performance Level Estimation (STAPLE) algorithm is employed to establish a consensus among eight freely accessible, non-deep learning-based methods for brain extraction, with the aim of generating silver standard masks. In 2019, [7], A 3D-U-Net was used by Hyunho et al. to strip the skull in brain MRIs. It

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represents an advancement over the earlier 2D-U-Net, which is rooted in advanced learning methodologies, especially convolutional neural networks. The method was compared against existing techniques using a publicly accessible MRI dataset of the brain.

It is shown that it can perform well on a level comparable to a specific deep learning algorithm with an average Dice coefficient (ADC) of 0.9903, a sensitivity of 0.9853, and a specificity of 0.9953. In addition, in 2022 Paredes-Orta et al. [8] recommended a three-step process for skull stripping. A maximum tree framework is first created to capture regional peaks ranking by employing the T1 MRI scan. Second, a series of morphological operations, called hyperconnected apertures, are used in order to remove small and isolated regions while preserving larger connected regions for the purpose of making a distinction among the brain and skull tissue. Lastly, a thresholding is carried out to make the final brain mask. The suggested approach obtained a 0.9416 Dice similarity coefficient (DSC) when looking at the NFBS dataset.

In 2022, [9], Pei et al. A collective neural network (CoNet) has been developed, which is based on a 3D convolutional neural architecture (3DCN), intended for executing brain extraction on multiparametric MRI images (mpMRIs).The efficacy is rigorously assessed through the implementation of the suggested technique across a total of 15 combinations of imaging modalities. The results show that the use of all modalities yields the highest presentation in skull stripping. In 2023, [10] Tamara et al. proposed a novel technique for skull stripping that enhances the contrast of brain images through the use of Adaptive Gamma Correction (AGC). This technique dynamically modifies its parameters according to the input image's properties. Additionally, The proposed skull stripping technique encompasses the largest connected components, a morphological image processing approach, and image multiplications.

The research employed the BrTSH::Brain Tumor Detection 2020 dataset, revealing that the techniques for image enhancement and skull removal are successful, achieving a 96% accuracy rate. In 2023, Azam et al. [11] studied a deep learning method to automate the skull stripping of MRI brain images completely. Traditional segmentation techniques have evolved immensely and are now joined with CNN. They presented and evaluated a modern version of the deep learning framework — notably based on Mask Region CNN (Mask–RCNN), suitable for numerous anatomical orientations of brain MR images. In 2023, [12]. Rasha et al. proposed a procedure that uses MRI images to evaluate and build 3D models that distinguish the skull from the brain with the brain intact. The principal steps to create this model are to take away the skull in three positions - axial, sagittal, and coronal, and test the model with untrained data. For the NFBS dataset, the evaluation result is a dice score of 99.9%. Likewise, training results indicate 98% accuracy and a 98.4% F1 score on the training dataset. Moreover, the external testing set IBSR also achieved a dice score of 99.9%. In 2023, [13], Mehnaz et al. suggested the utilization of a cutting-edge nnU-Net - based deep learning framework for brain MRI skull stripping. The proposed methodology was evaluated utilizing two publicly available datasets: The Neurofeedback Skull-stripped Repository (NFBS), which comprises normal brain MRI scans, and The Cancer Genome Atlas (TCGA), which contains MRI scans of brain tumors. In the NFBS dataset, the proposed method achieved an ADC of 0.9960, with a specificity of 0.9996, a sensitivity of 0.9999, and a 0.9762 accuracy. The ADC for the TCGA brain tumor dataset was 0.9296, with sensitivity of 0.9288, specificity of 0.9866, and accuracy of 0.9762. In 2024, Arwa and Ashwaq [14], introduced this new model called the fully integrated “3D Attention Residual Recurrent U-Net” (3D-ARR-U-Net). It pulls recurrent mechanisms, attention, and residual parts right into the standard U-Net structure. All that helps boost accuracy and efficiency when it comes to stripping the skull from brain MRI scans. The training happened on the NFBS benchmark dataset. Then for checking how it did, they looked at things like IoU, sensitivity, specificity, precision, DSC and accuracy. The experiments turned out strong. This strategy easily outperforms the current ones. It achieved a 1.0000 DSC score. The sensitivity was 0.9811. IoU was also 0.9811. The specificity was 0.9971. At 0.9971, precision matched that. Additionally, accuracy peaked at 0.9979.

The current skull stripping techniques either employ traditional methods that are highly sensitive to noise or advanced deep learning-based techniques that demand high computational resources. In many skull

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stripping techniques, the results heavily rely on inaccurate ground truth masks, as well as the availability of limited data, which makes the techniques difficult to generalize.

3. RELATED TOPICS

3.1. U-Net Architecture

U-Net is a well-known convolutional neural network model originally developed for the image segmentation task back in 2015. It was constructed by Ranneberger et al., [15] at the department of computer science at the university of Freiburg, Germany. The predominant architecture of most approaches for brain tumor segmentation and classification tasks is U-Net. The U-Net is also known for its performance with limited records.

Encoder course, bridge layer, linguist course, and output coating are the four components that make up the U-Net design, which gets its name from its attractive U-shaped composition. The U-Net sketch is displayed in Fig.1.

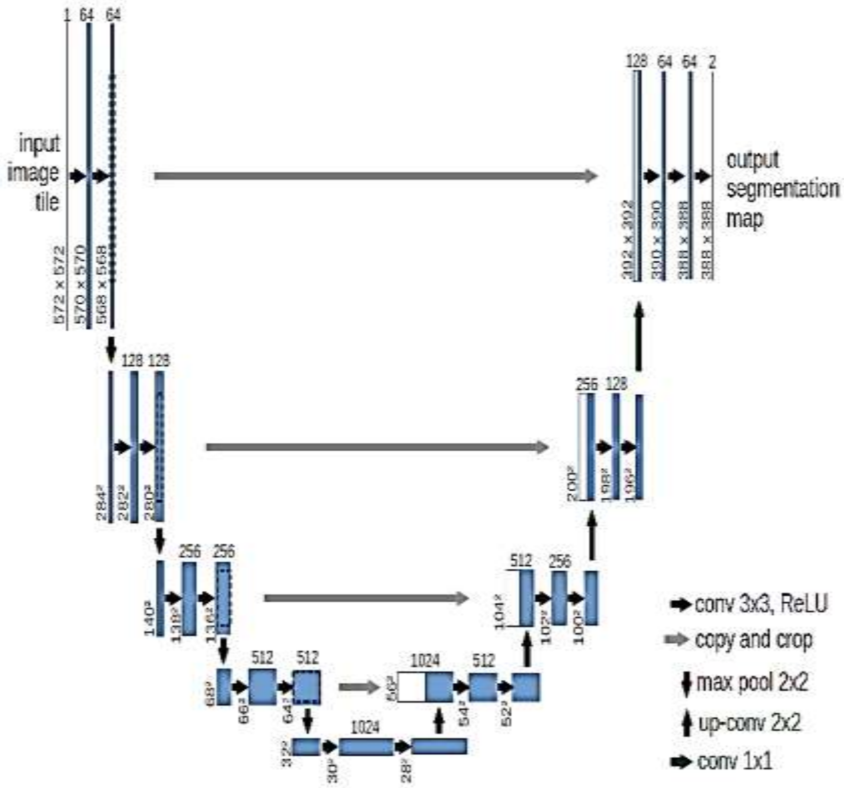

Fig.1. Shows the block diagram for U-Net. Each layer's channel count is systematically indicated above it [15].

3.2. Residual Mechanism

In very deep networks, residual mechanisms are typically employed as a method for addressing the degradation problem [16]. In the case when a deep network's accuracy reaches a saturation point and after that sharply declines as the network depth rises, it presents a degradation issue [17]. The core concept of residual networks lies in the employment of convolution blocks that feature skip or shortcut connections. These connections allow the network to bypass at least one layer, facilitating a direct passage of information from one layer to the next. In mathematical terms, the output of a residual block is not merely a transformation of the input, but a sum of the input alongside the transformations performed within the block [18]. As multi-layer NN's depth increases, degradation could become a problem and hinder training [19]. Fig.2 displays the residual block from design of residual network.

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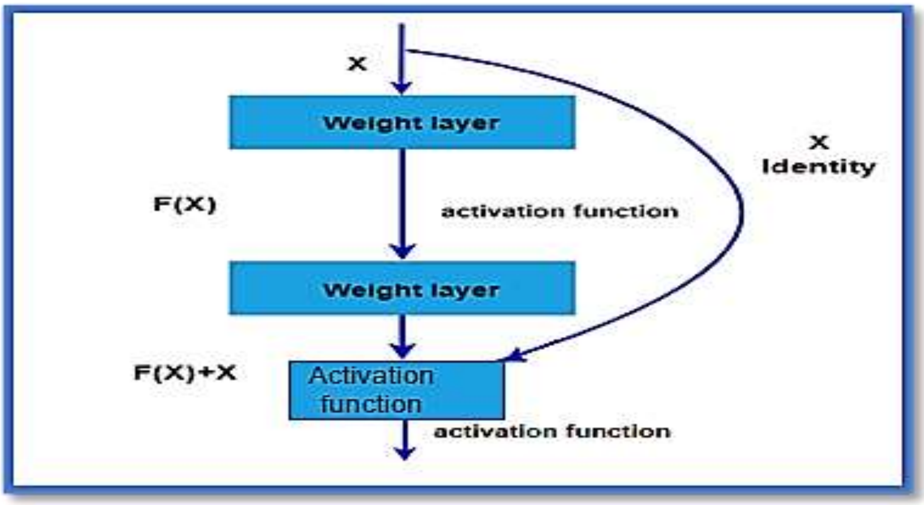

Fig. 2. Residual Network architectural design.

In 2016, He et al. introduced the a residual neural network metho to tackle this problem and enhance the training process [1]. They implemented adaptive skip connections within the remaining blocks to maintain low-level information; this network effectively addresses the vanishing gradients issue. As activations from previous layers can be sent straight to layers that come after them through identity mapping links. The concatenation operator combines the residual convolution block's input and output. Apart from improving communication, the model's convergence to the global minimum is accelerated by the residual network. One of the two any residual element in residual NN can be characterized by equations (1) and (2).

$$Y_i = F(x_i, w_i) + h(x_i) \quad (1)$$

$$X_{i+1} = f(y_i) \quad (2)$$

where $h(x_i)$ represents the identity mapping function, F(.) is the residual function, and $f(y_i)$ is the activation function. An illustration of this would be if the input and output of the ith residual unit were h (x_i)= x_i and x_i and x_{i+1}.

3.3. MRI Skull Stripping Dataset

In total, 155 brain MRI images that show tumors and 95 non-tumor brain MRI images were arranged in the respective folders within the Kaggle dataset that was used for skull stripping [20]. The NFBS database includes 125 anatomical MRI images of participants aged 21 to 45; each of the 124 subjects was carefully skull-stripped by experts. The brain MRI scanning data was collected via a T1-weighted (T1w) model. Each person within the training dataset was assigned ground truth labels manually. The NFBS contains various T1-weighted (T1) MRI samples such as these which represent a sequence of two-dimensional images from the axial, coronal, and sagittal planes of the brain. These slices, when combined, may represent the whole of the brain in three dimensions and may be used as a template in other neuroimaging research studies. The dimensions of each MRI scan are 256 × 256 × 192, in which the first two figures show the size of the 2D slices, while the last figure shows the total number of slices in that scan. Each volume of MRI shows only the voxel size (1×1×1) mm³. Fig. 3 gives illustrative examples from the NFBS dataset.

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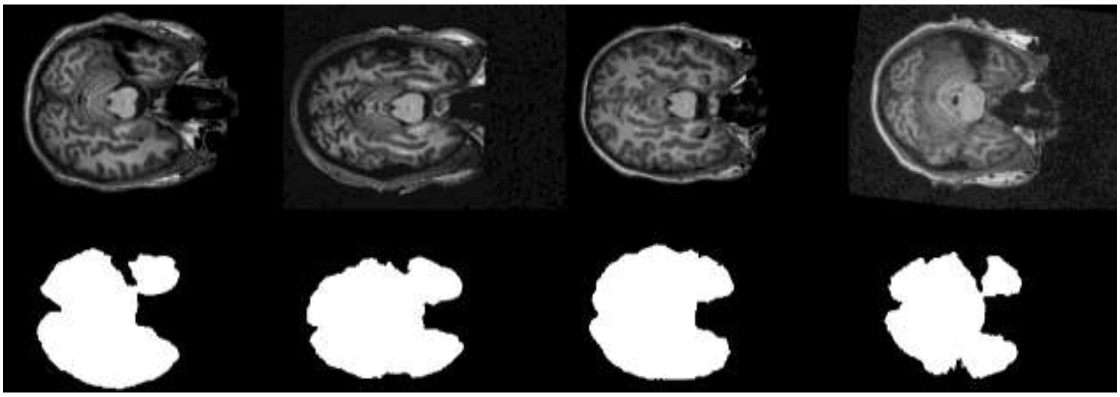

Fig.3. The NFBS samples. (a) the images of T1 MRI (b) the ground truth.

4. PROPOSED SYSTEM

An outline of the suggested method's system is shown in Fig. 4 which helps to clarify the process.

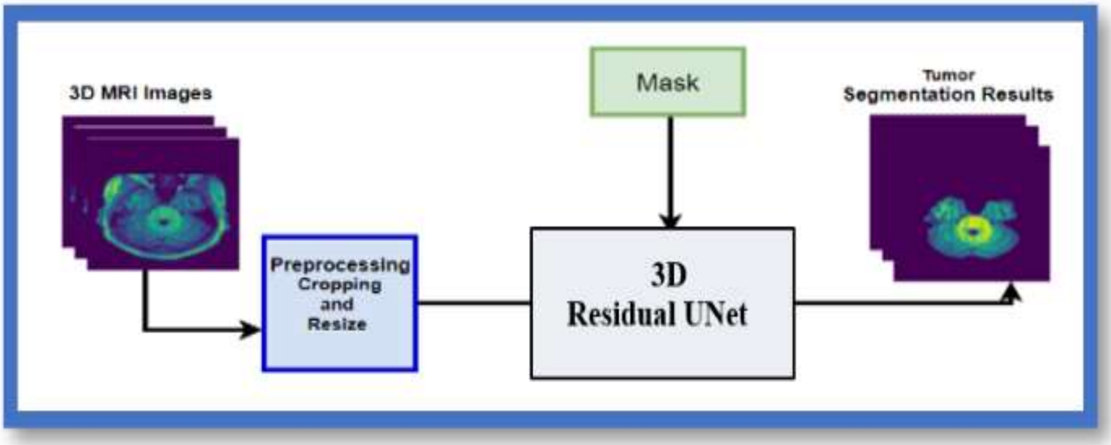

Fig. 4. Block diagram of modified 3D Residual U-Net.

4.1 3D MRI Pre-processing

As seen below, we employ a series of pre-processing techniques in this study, such as cropping, resizing, and adaptive Anisotropic diffusion filtering.

4.1.1. Anisotropic Diffusion Filtering (ADF)

Brain magnetic resonance imaging (MRI) undergoes pre-processing through the application of an anisotropic diffusion filter (ADF) prior to executing skull stripping and contrast enhancement procedures. ADF removes unwanted noise from MRI scans while maintaining the boundaries of current structures, followed by the extraction of the skull to discard non-brain tissues and the enhancement of contrast for better visual clarity. Anisotropic diffusion filter has been successfully employed in the context of image processing to remove high frequency noise while conserving the main edges of existing objects. In its discrete form, ADF is an iterative algorithm that simulates the diffusion process by equation (3):

$$I_s^{t+1} = I_s^t + \frac{\lambda}{|\eta_s|} \sum_{p \in \eta_s} g\left(|\nabla I_{s,p}^t|, \gamma\right) \nabla I_{s,p}^t \qquad (3)$$

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where g (·) is an ESF, $I_{s,p}^{t}$ is the magnitude of the image directional gradient from pixel s to p at instant t, η_s represents the set of adjacent pixels of s, λ is a scalar associated with the diffusion rate, γ is a positive constant chosen based on the desired smoothing level, and I_{s}^{t} is the intensity of a pixel s from image I at instant t. An approximation of the directional gradient $I_{s,p}^{t}$ is It $I_{p}^{t} - I_{s}^{t}$. When pixel information and the iteration number are not relevant to the context, we shall substitute x for $I_{s,p}^{t}$ in order to simplify the notation [21,22].

4.2 Proposed 3D Residual U-Net

Fig. 5 depicts the encoder and decoder, the two primary components of the network. The number of filters used during neural network training dictates which blocks show up in the first and end sections. Section three consists of a loop that connects parts two and three. Layers are stacked one on top of another in each encoding block, with each layer providing output to the block behind it and receiving input from the one before it. Additionally, each block in the encoder and each corresponding block in the decoder are connected. Multiple successive layers, such as max pooling, convolution, batch normalization, dropout, and add layer, are present in every set. To put it another way, the encoding process is made up of numerous blocks, each of which processes the input in a certain way before passing the results on to the following block. The complexity of the layer is determined by how many filters the neural network learns during training. After passing through each level of the network, the input is finally sent to the decoding part by means of the bridge. The decoding procedure, the inverse of the encoding process, takes as input the encoded data that was received from the bridge. Layers apply inverse. Each set of layers performs a series of operations, such as convolution, batch normalization, dropout, add layer, and max pooling. By applying a linear function to each layer's output, the convolution process makes the network more linear. By normalizing each layer's output, batch normalization facilitates processing the one beneath it. The vanishing gradient problem, in which the training process is impeded by the gradient values being so small during back propagation, is resolved by the dropout approach. Layer addition can be used to blend the output of two or more layers, while maximal pooling can be used to down-sample the output of one layer to make it smaller.

Table illustrates the suggested hyperparameters used in the enhancement of U-net for skull stripping segmentation.

Table 1 Brain Tumour segmentation and Classification Using Enhancement U-net Parameters

Hyperparameters	Brain tumor segmentation and classification
Input Size	128 ×128× 128 × 3
Learning rate	0.001
Batch Size	2
Hidden Layer - Activation Function	ReLU
Loss Function	Focal + dice loss
Optimizer	ADAM
Epochs	100
Dropout	0.2
Output Layer activation fun.	SoftMax
Output Size	128 x 128 x 128 x 4

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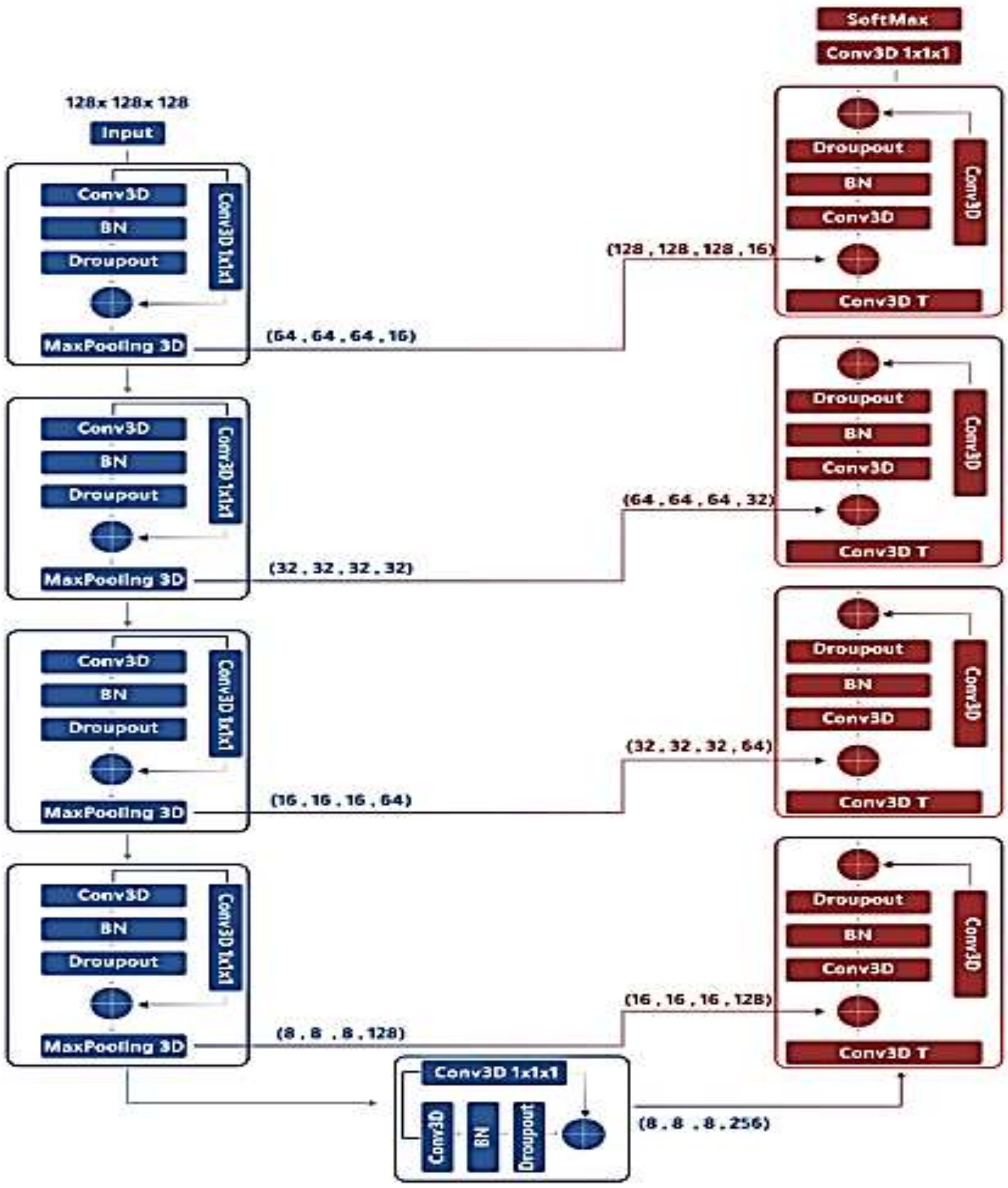

Fig. 5. Framework of Proposed Internal Residual U-Net.

A. Encoder

The encoding step partitions the network into several resizable pieces, reliant on the size of image in addition to the filters used. These partitions have an immediate effect on the parameters numbers used and the neural network performance. As seen in Figure 8, the proposed approach involves attaching a skip connection to every block. A 1×1×1 convolutional layer is used to run a copy of the input in order to keep the block's outputs from losing gradients. After that, the output is combined with this duplicate. To cut down on computation and training time, one convolution from each block's layers is eliminated. With no enhancements, the network's total number of convolutional layers is 21, This has fewer layers than the original, conventional U-Net. This improves the efficiency of the network's learning process, although learning takes time or a powerful GPU device, but less than what required in stander U-Net. Fig. 6 illustrates the several levels included in the encoding block. The first step is to split the input in half. The initial copy is fed into the 3×3×3 convolutional layers in a sequential fashion. After that, normalize batches, which

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enables us to employ significantly higher learning rates and accelerates network training. Upon completion of hierarchical down sampling, the output of both copies is then combined. A 1×1×1 convolution is applied to the second copy of the input in order to allocate each input pixel to its matching output pixel across all channels. The outputs of the first and second copies are combined after all actions on them are finished. MaxPooling3D is used to lower the output size in order to obtain the U-shaped network. Following the conclusion of each.

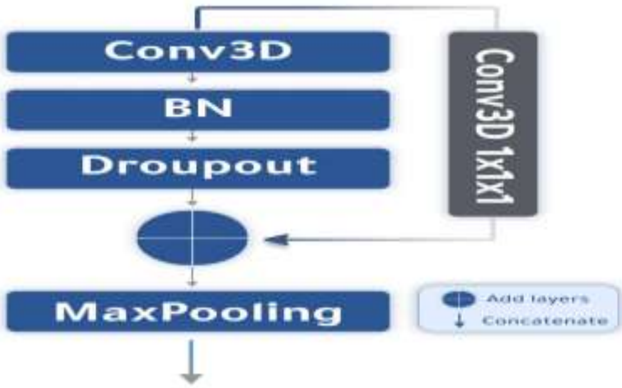

Fig. 6. Encoder block of proposed 3D Residual U-Net.

B. Decoder

Figure 7 depicts the decoding process, which is different from the encoder portion. Two blocks make up the input: one from the prior block and the other from the block that corresponds to it in the encoding portion. The first half enters the convolutional transpose and doubles the input size to match the second input from the encoding stage. The two inputs are then merged. On the outcome of the prior addition, the next actions are carried out in order. The output of the preceding operation is replicated and subjected to the same batch normalization, dropout, and convolutional operations as the encoding portion. In the end, this is combined with the second copy, which has already made its way into the 1×1×1 convolutional layers.

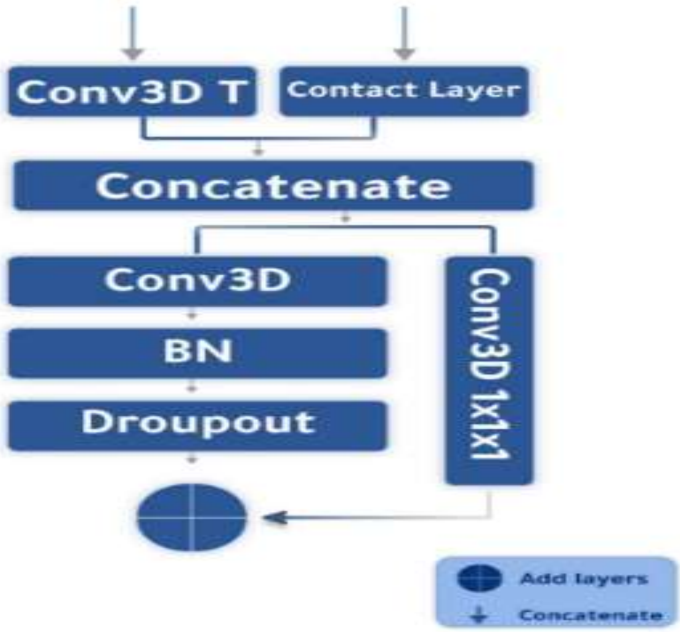

Fig. 7. Decoder block of proposed 3D Residual U-Net.

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C. Training Hyper-parameters

I. Dataset split: This step is done after the pre-processing the eye image to obtain the iris only as the data is split into 20 % testing and 80% training.

II. Loss function: In this model, the sparse multiclass cross entropy loss is used according to the equation ($Dice\_loss + Focal\_loss$) because the fact that memory needs to complete the training faster.

III. Optimizer: Adaptive Moment Estimation (Adam) described in the previous chapter is used. the learning rate is 0.0001.

IV. Batch size: the training data is divided into batches to be trained. The minibatch size used in this model is 2.

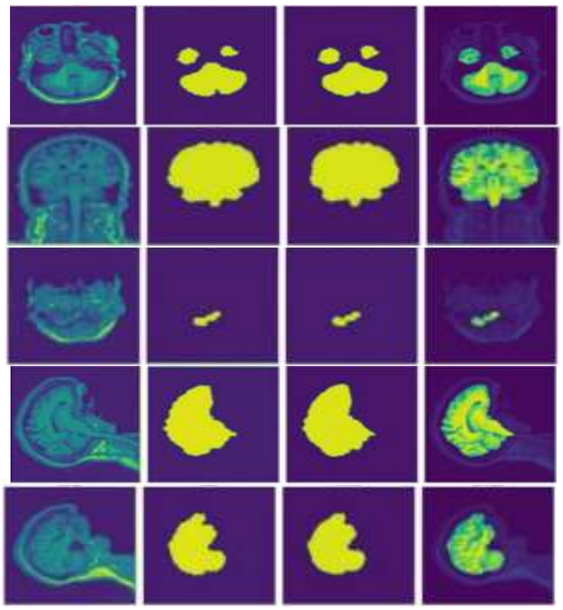
V. Epochs: the number of epochs used to train NFBS dataset is 100 to get the required accuracy.

VI. Early stopping: in designing this network, the early stopping technique was used to eliminate the overfitting problem where training stops if the validation accuracy decreases for the last 5 epochs.

The model proposed in the study demonstrates good performance but lacks generalizability, as it was only tested on a few data sets. It also relies on several pre-processing techniques, which may not be very practical, and the computational costs may be high, as well as the fact that the hyperparameters are set empirically, and the model has not been fully validated, especially in pathological cases.

5. RESULTS AND DISCUSSION

Using the NFBS data set, the suggested skull stripping technique is trained and evaluated. The technique is used once without pre-processing the images and once with preparation to determine how much the desired outcomes are impacted by image pre-processing. By assessing DSC, IoU, precision, sensitivity, specificity, and accuracy, the method's effectiveness was evaluated. Fig. 8 displays skull stripping samples results from the dataset validation in the NBFS set. The visual representation depicts the degree to which the outcomes align with the actual values.



(a) (b) (c) (d)

Fig. 8. skull stripping Illustrations results on the NBFS validation set . (a) the original T1-weighted MRI image, (b) the reference standard, (c) the anticipated brain mask, and (d) the isolated brain.

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The suggested 3D Residual U-Net technique, 3D U-Net, MHF method, and MVU-Net method mean deviations are compared in Table 2.

Table 2. Comparison of mean deviation. Th highest values are highlighted in bold.

Method	Sensitivity	DSC	Specificity
3D U-Net [7]	0.9853	0.9903	0.9953
MHF [8]	–	0.9600	–
MVU-Net [23]	0.9763	0.9681	0.9954
[3D_Att_Res_U-Net [14]	0.9943	0.9961	0.9916
Proposed: 3D Residual U-Net with ADF	0.9974	0.9993	0.9983
Proposed: 3D Residual U-Net without ADF	0.9437	0.9062	0.9887

According to the table 1, the proposed skull stripping using 3D Residual U-Net approach performed better than previous research, especially in terms of sensitivity and DSC. The training and validation datasets' accuracy, sensitivity, precision, specificity, and intersection over Union (IoU) are shown in Figure 9

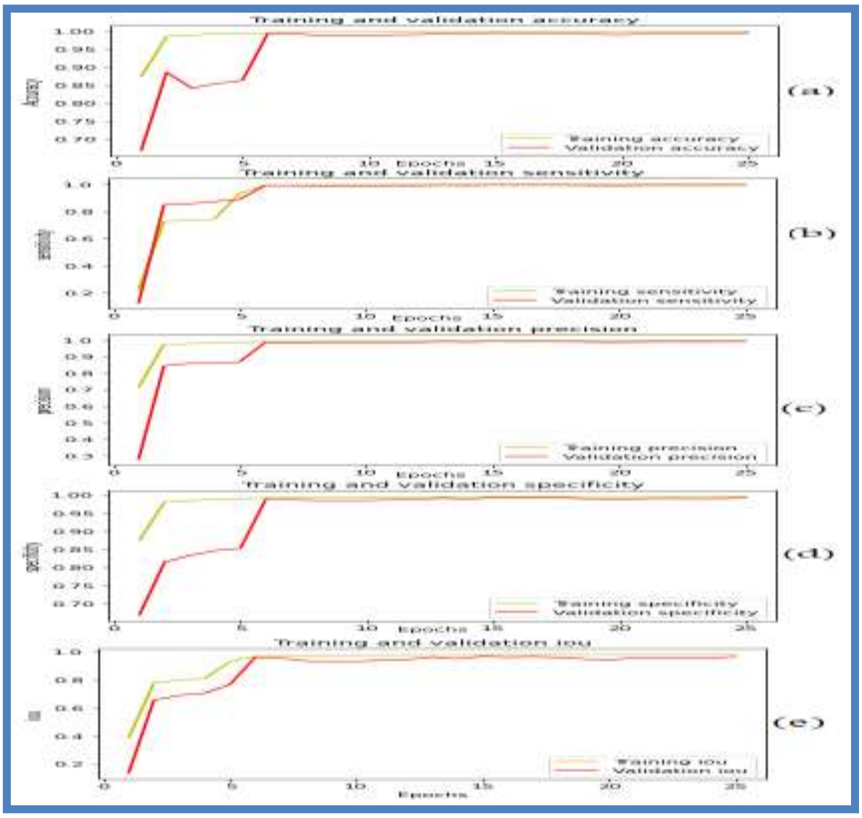

Fig. 9. Illustrates the (a) Accuracy, (b) Sensitivity, (c) Precision, (d) Specificity, and (e) Intersection over Union (IoU) for both the training and validation datasets of the NFBS dataset.

6. CONCLUSIONS

The present paper presents the 3D Residual U-Net architecture model for 3D MRI skull stripping. Its improved performance is largely attributed to two major architecture features. Initially, residual blocks were created to enable the network to focus on learning the residual mapping between inputs and outputs, as opposed to a direct mapping. This way the model learns residual mappings efficiently using this method.

For the second reason, an anisotropic diffusion filter (ADF) reduces noise in MRI images while maintaining the edges of present objects. This pre-processing method has been verified to enhance segmentation results, demonstrating its effectiveness.

Experimental results validate the superiority of the proposed strategy over existing state-of-the-art models. The model attains a remarkable dice score of one, all without requiring extra data enhancement or follow-up processing methods. Forthcoming study on brain tumor segmentation will employ the proposed methodology, expanding its potential applications in medical image processing.

REFERENCES

[1] He, K., Zhang, X., Ren, S., & Sun, J., *Deep Residual Learning for Image Recognition*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770–778, 2016. doi.org/10.48550/arXiv.1512.03385

[2] Oktay, O., Schlemper, J., Le, H. N., et al., *Attention U-Net: Learning Where to Look for the Pancreas*. arXiv preprint arXiv:1804.03999, 2018. doi.org/10.48550/arXiv.1804.03999

[3] Ronneberger, O., Fischer, P., & Brox, T., *U-Net: Convolutional Networks for Biomedical Image Segmentation*. MICCAI, 234–241, 2015. doi.org/10.48550/arXiv.1505.04597

[4] Alom. M. Z., Yakopcic. C., Hasan. M., Taha.T. M., and Asari. V. K., "*Recurrent residual u-net for medical image segmentation*," Journal of Medical Imaging, vol. 6, no. 1, p. 014006, 2019. doi: 10.1117/1.JMI.6.1.014006

[5] Xu G, Wang X, Wu X, Leng X, Xu Y. *Development of residual learning in deep neural networks for computer vision*: A survey. Eng Appl Artif Intell. 142:109890, 2025. https://doi.org/10.1016/j.engappai.2024.109890

[6] Lucena O, Souza R, Rittner L, Frayne R, Lotufo R. *Convolutional neural networks for skull-stripping in brain MR imaging using silver standard masks*. Artif Intel Med.;98:48–58, 2019. https://doi.org/10.1016/j.artmed.2019.06.008

[7] Hwang H, Ur Rehman HZ, Lee S. *3D U-Net for skull stripping in brain MRI*. Appl Sci. 9(3):1–15, 2019. doi.org/10.3390/app9030569

[8] Paredes-Orta C, Mendiola-Santibañez JD, Ibrahimi D, Rodríguez-Reséndiz J, Díaz-Florez G, Olvera-Olvera CA. Hyperconnected openings codified in a max tree structure: *An application for skull-stripping in brain MRI T1*. Sensors (Basel). 22(4):1378, 2022. https://doi.org/10.3390/s22041378

[9] Pei L, Ak M, Tahon NHM, Zenkin S, Alkarawi S, Kamal A, et al. *A general skull stripping of multiparametric brain MRIs using 3D convolutional neural network*. Sci Rep.12(1):10826, 2022. https://doi.org/10.1038/s41598-022-14983-4

[10] Dawood TA, Hashim AT, Nasser AR. *Automatic skull stripping of MRI head images based on adaptive gamma transform*. Math Model Eng Probl. 10(1):304–310, 2023. https://doi.org/10.18280/mmep.100136

[11] Azam H, Tariq H, Shehzad D, Akbar S, Shah H, Khan ZA. *Fully automated skull stripping from brain magnetic resonance images using Mask RCNN-based deep learning neural networks*. *Brain Sci.* 13(9):1255, 2023. https://doi.org/10.3390/brainsci13091255

[12] Nayyef RH, Al-Tammi MSH. *Skull stripping based on the segmentation models*. J Eng. 29(10):74–98, 2023. https://doi.org/10.31026/j.eng.2023.10.05

[13] Tabassum M, Al Suman A, Russo C, Di Ieva A, Liu S. *A deep learning framework for skull stripping in brain MRI*. In: Proc 45th Annu Int Conf IEEE Eng Med Biol Soc (EMBC),2023. https://doi.org/10.1109/embc40787.2023.10340846

[14] Ridha AS, Hashim AT. *Improves brain skull stripping using attention residual recurrent 3D U-Net*. In: Swaroop A, Virdee B, Correia SD, Polkowski Z, editors. Proceedings of Data Analytics and Management. ICDAM 2024. Lecture Notes in Networks and Systems. Vol. 1300. Singapore: Springer; p.1-15, 2025. https://doi.org/10.1007/978-981-96-3361-6_22

[15] Ronneberger O, Fischer P, Brox T. U-Net: *Convolutional networks for biomedical image segmentation*. In: Med Image Comput Comput-Assist Interv – MICCAI 2015: 18th Int Conf, Munich, Germany, Oct 5–9, 2015, Proc, Part III. 234–241, 2015. https://doi.org/10.1007/978-3-319-24574-4_28

[16] Iqbal S, Ghani MU, Saba T, Rehman A. *Brain tumor segmentation in multi-spectral MRI using convolutional neural networks (CNN)*. Microsc Res Tech. 81(4):419–427, 2018. https://doi.org/10.1002/jemt.22994

[17] Zhao X, Wu Y, Song G, Li Z, Zhang Y, Fan Y. *A deep learning model integrating FCNNs and CRFs for brain tumor segmentation.* Med Image Anal. 43:98–111, 2018. https://doi.org/10.1016/j.media.2017.10.002

[18] Abd-Ellah MK, Khalaf AAM, Awad AI, Hamed HFA. TPUAR-net: *Two parallel U-Net with asymmetric residual-based deep convolutional neural network for brain tumor segmentation*. Lect Notes Comput Sci (LNCS). 11663:106–116, 2019. https://doi.org/10.1007/978-3-030-27272-2_9

[19] Derikvand F, Khotanlou H. *Patch and pixel-based brain tumor segmentation in MRI images using convolutional neural networks*. 5th Iran Conf Signal Process Intell Syst (ICSPIS),1–5. 2019. https://doi.org/10.1109/ICSPIS48872.2019.9066097

[20] Preprocessed Connectomes Project. *NFBS skull-stripped repository*. Available from: Accessed Mar 9, 2024. http://preprocessedconnectomesproject.org/NFB_skullstripped/

[21] Palma CA, Floares JB, Popescu F. *Anisotropic diffusion filtering operation and limitations—Magnetic resonance imaging evaluation*. IFAC Proc Vol. 47(3):10645–10650, 2014. https://doi.org/10.3182/20140824-6-ZA1003.02347

[22] Maurya R, Wadhwani S. *An efficient method for brain image pre-processing with anisotropic diffusion filter and tumor segmentation*. Optik (Stuttg). 265:169474, 2022. https://doi.org/10.1016/j.ijleo.2022.169474

[23] Fatima A, Madni TM, Anwar F, Janjua UI, Sultana N. *Automated 2D slice-based skull stripping multi-view ensemble model on NFBS and IBSR datasets*. J Digit Imaging. 35(2):374–384, 2022. https://doi.org/10.1007/s10278-021-00560-0